430.19

Differentially Variable Component Analysis (dVCA): A New Tool For Understanding Brain Responses

430.19

KH Knuth[1], AS Shah[2,3], WA Truccolo[4], M Ding[5], SL Bressler[5], CE Schroeder[2,3]

[1]Computational Sciences Division, NASA Ames Research Center, Moffett Field, CA 94035
[2]Department of Neuroscience, Albert Einstein College of Medicine, Bronx, NY 10461
[3]Cognitive Neuroscience & Schizophrenia Program, Nathan Kline Institute, Orangeburg, NY 10962
[4]Neuroscience Department, Brown University, Providence RI 02912
[5]Center for Complex Systems and Brain Sciences, Florida Atlantic University, Boca Raton FL 33431

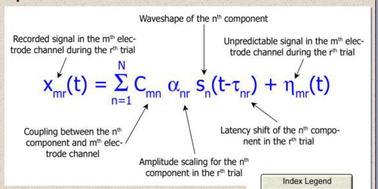
Single-Trial Analysis using dVCA

We introduce a new tool for understanding single-trial evoked responses called Differentially Variable Component Analysis (dVCA). This technique is based on the facts that neural responses evoked by a stimulus vary in amplitude and latency from trial-to-trial, and that different neural sources exhibit different degrees of variability. Rather than relying on artificial assumptions such as independence of the sources, dVCA exploits this differential variability to tease apart the responses from different neural sources. By applying dVCA one obtains a set of components, whose linear combination describes each single-trial response, along with their corresponding single-trial amplitudes and latencies. In addition, by accurately describing the evoked responses, the residual signal can be used to study ongoing oscillations. We will discuss the dVCA algorithm, its application, and highlight its advantages by describing some exciting new results such as: evidence of multiple response mechanisms, coupling between neural sources, and relations between evoked responses and ongoing oscillations.

The mcERP Model

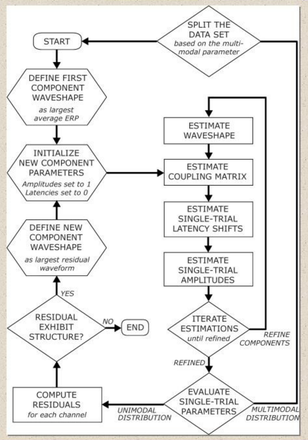
The multiple component event-related potential (mcERP) model underlies the dVCA technique.

A single-trial ERP consists of a sum of evoked components, which are relatively time-locked to the stimulus plus some unpredictable signal, which may be induced activity or noise.



Each component is allowed to vary in both amplitude and latency from trial to trial.

The dVCA Algorithm



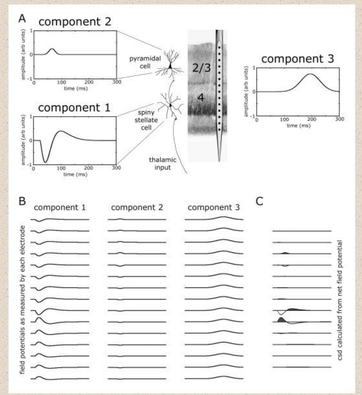
Bayes' theorem is utilized to express the posterior probability of the model above.

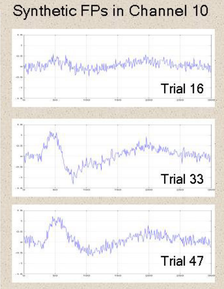
An iterative fixed-point algorithm is derived to estimate the most probable parameter set for our model.

The complexity of the brain responses precludes the use of the algorithm as an automated procedure. However, as we will show, interesting results are readily obtained when using dVCA as an analysis tool.

Synthetic Data

Synthetic intracortical field potentials (FPs) were generated to assist us in fully characterizing the dVCA algorithm. These data were modeled after what we believed would be the major responses to a red light flash in macaque V1.





50 experimental trials were simulated by randomly choosing the single-trial characteristics of each component and adding Gaussian noise.

Relative SNRs of the three components are 0 dB, -13.9 dB, -5.2 dB.

The amplitude variability was sampled from a log-normal distribution with sample characteristics $\mu_{amp} = 1.0$ and $\sigma_{amp} = 1.0$

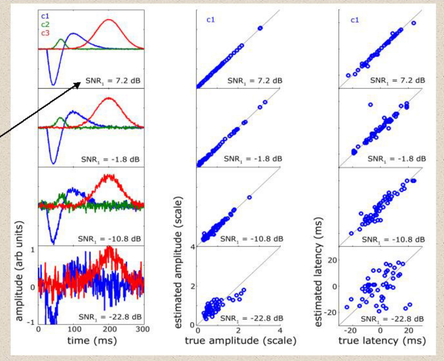
The latency variability was sampled from a Gaussian with $\mu_{lat} = 0$ ms and $\sigma_{lat} = 10.0$ ms.

dVCA is Robust to Noise

The SNR was varied by increasing the noise level in the synthetic data.

C1 SNR is reported.

Note how the single-trial estimates degrade with increasing noise.



Component waveshapes, amplitudes and latencies can be estimated down to about -20 dB for white Gaussian noise and about -7 dB for highly correlated noise (not shown).

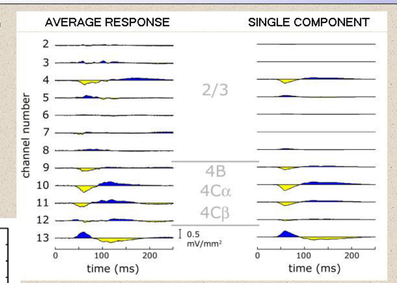
Real Data

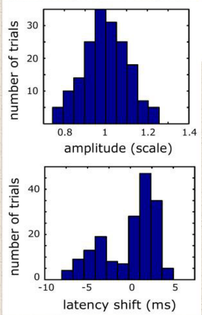
171 trials were collected from primary visual area V1 of an awake macaque monkey by acutely inserting a linear-array electrode into the brain. Field potential activity was sampled continuously at 2000 Hz, while the subject was presented with randomly interspersed standard and target visual stimuli at an average rate of 2/sec. The standard visual stimulus was of a 10-μs, red-light flash, and the target varied slightly in intensity. The monkey released a lever after each presentation of the target stimulus to earn a drop of juice.

Revealing Two Response Modes

On the left is the CSD of the average response.

On the right is the CSD of a single component, which was estimated using dVCA.





A histogram of the single-trial amplitudes shows little amplitude variability, $\sigma_i = 0.104$.

Whereas, a histogram of the single-trial latency reveals two response modes: early and late. The early mode is at -4.625 ms and the late mode is at 2.125 ms.

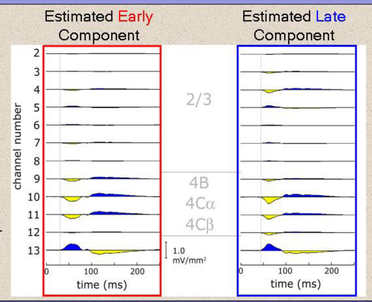
The ratio of late to early modes is about 7:3

See poster 429.5 for details on a second data set displaying similar attributes.

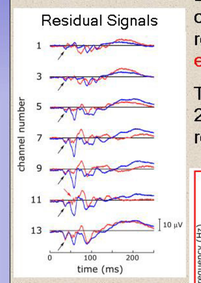
Splitting the Data Set

We can use the single-trial latencies to split the data set and study the two early and late responses separately.

The CSD plots reveal different laminar profiles of the current sources and sinks with the late response having a larger supragranular (Layers 2/3) activation.

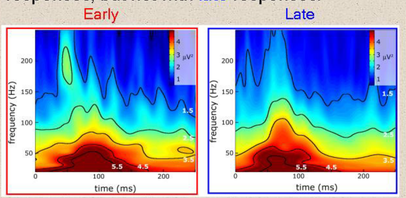


The Residual Signals

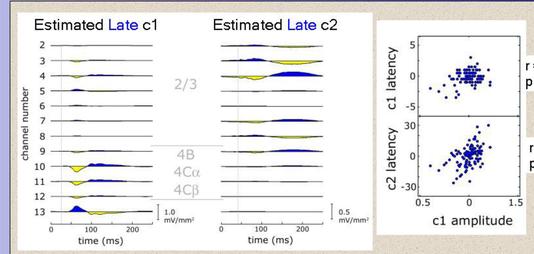


By subtracting the modeled components, one obtains an accurate picture of the unmodeled residual signals. Clear differences between the early and late subsets can be identified.

Time-frequency plots highlight an interesting 200 Hz oscillatory burst associated with early responses, but not with late responses.



Correlations among Components



By estimating multiple components (here from the late subset), we can examine correlations among their single-trial parameters thereby quantifying their dynamical interactions. When c1 is big, c2 is late.

Summary

Brain responses are dynamic, state dependent, and change over time. DVCA relies on these trial-to-trial changes to separate, identify and characterize single-trial responses from multiple simultaneously active sources. Different responses modes as well as dynamical interactions and interdependencies among components can be studied by examining these single-trial characteristics. By subtracting the estimated components, accurate ongoing activity, such as induced oscillations can be further examined.

Acknowledgements

We thank Dr. Peter Lakatos, Dr. Istvan Ulbert, Dr. Ashesh Mehta, Tammy McGinnis, Noelle O'Connell, Aimee Mills, Dr. Len Trejo and Sam Clanton. The work was supported by the NASA IDU/IS/CICT Program, NASA Aerospace Technology Enterprise, NARSAD Young Investigator Award, NIH T32M07288, MH60358, MH64204, MH42900, and NSF IBN0090717.

Please visit **429.5** for more on the application of dVCA, and **485.19** (this afternoon) for a study of ongoing activity using dVCA.